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An agent-based model for diffusion of electric vehicles

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Abstract

The transition from fuel cars to electric cars is a large-scale process involving many interactions between consumers and other stakeholders over decades. To explore how policies may interact with consumer behavior over such a long time period, we developed an agent-based social simulation model. In this model, detailed data of 1,795 respondents have been used to parameterise an agent architecture that addresses different consumer needs and decision strategies. Numerical experiments indicate that effective policy requires a long-lasting implementation of a combination of monetary, structural and informational measures. The strongest effect on emission reduction requires an exclusive support for full battery electric cars and no support for hybrid cars.

1: Introduction

In the current age, in which global warming, oil-dependency and fluctuating oil prices govern research agendas, the transition to energy-efficient techniques is becoming increasingly important. Plug-in battery electric vehicles (PEVs) are one such promising solution.

The development of electric cars goes almost as far back as the first employment of automobiles in general. Around the turn of the 20th century, gasoline vehicles and electric vehicles (EVs) served distinct niches of personal transport in the USA without being direct competitors (Geels, 2004). While gasoline vehicles were mostly used for long-distance touring and racing, the earliest models easily stalled at low speeds. Electric vehicles therefore served as a safe choice for short distance travel at the eve of the automotive era. However, a range of market conditions in benefit of the gasoline car led to the overall dominance of fossil fuel technology.

In the course of the twentieth century, every consecutive endeavour to revive electric cars failed once the initial stimulus to do so was removed; during both World Wars, EVs were temporarily popular while gasoline supply was tight, while in the 1990s, the temporary willingness of car manufacturers to pursue EVs dwindled once regulation was loosened (Hoyer, 2008). However, just as the gasoline vehicle once won over the market because its characteristics were favourable from many different perspectives, it is possible that the diffusion of EVs might also thrive under similarly multi-perspective beneficial conditions.

One could argue that such conditions are currently being created. First, in order to reduce carbon emissions and reliance on fossil fuels, multiple countries have introduced formal regulations as well as financial incentives for businesses and consumers to push the development and diffusion of electric vehicles forward. Second, multiple parties are involved in the spread of charging infrastructure, such as governments, energy producers and car manufacturers. For example, Renault and Tesla have taken initiative in installing recharge stations available to their customers (Ayre, 2016; Fleet, 2016). Third, technological advancements in the past decades have resulted in a new generation of electric cars employing lithium-ion batteries that carry four times more intensity than their lead acid historical counterparts and at the same time increase the cycle life-time by a similar degree (Rajashekara, 2013). All these developments change the transportation landscape and potentially create positive conditions for the adoption of (full) electric vehicles.

Currently hybrid vehicles, plug-in hybrid vehicles (PHEVs) and full battery electric vehicles (BEVs) are on the market. One advantage of the PHEV is that once its battery is depleted, the driver may shift towards the combustion engine and continue driving in a regular fuel mode. This, however, still results in emissions of particulate matter, CO₂, as well as other greenhouse gases, in contrast to a BEV. In this paper we only address tailpipe emissions from the car. Obviously, the degree to which electricity has been generated using sustainable resources has a positive indirect effect on the decrease of emissions. We assume that, in line with sustainability and climate goals, the proportion of sustainably generated electricity will increase in the future, leading to even more sustainable BEVs compared to gasoline vehicles. However, because this effect is indirect, we will not include it into our modelling of BEV diffusion.

An important question is which policies would most effectively facilitate a decrease in emissions from car traffic. A variety of policy measures are available, such as monetary measures (including subsidies, tax exemptions, and the like), structural measures (such as installation of charging infrastructure), and provision of information, for example, on the environmental impact of vehicles, their functional characteristics and market shares.

A second important question is which combination of policy measures may be most effective in facilitating lower emissions. For example, do structural measures complement or substitute monetary measures, and is information effective in combination with structural or monetary measures, or both? A third question concerns the target of policies. Should governments stimulate the use of both PHEVs and BEVs, as they both have lower emissions than gasoline fueled cars, or is it better to stimulate exclusively the use of BEVs since these are 0% emission vehicles?

To date, various policy regimes have been pursued around the globe. For example, in Europe, Norway follows a stringent policy by predominantly stimulating the use of zero-emission vehicles, BEVs. As of October 2014, 94.5% of the country's electric fleet consisted of BEVs and only 5.5% consisted of PHEVs (Grønn Bil, 2014). The Netherlands pursues a looser policy, which favours subsidisation of the purchase and use of a wider range of low-emission vehicles, i.e. both BEVs and PHEVs. In contrast to Norway, in 2014 only 14% of the Dutch electric personal car fleet was a BEV, the other 86% being PHEVs

(RVO, 2014). These numbers lead to another important question: how stringent should government policies be in order to be most effective in lowering tailpipe emissions from traffic? To answer these questions, one has to know which characteristics of BEVs and PHEVs are most appreciated by consumers and which characteristics hinder them most, in order to be able to devise a policy that increases the advantages and decreases the barriers to adoption most effectively.

Available studies shed light on consumers' various motives to purchase a car with a particular propulsion system, including functional, symbolic and hedonic aspects (Schuitema et al., 2012; Bockarjova & Steg, 2014; Noppers et al., 2014). However, even being armed with information about individual preferences for alternative vehicles, it is difficult to make plausible predictions about consumers' future behavior, due to a number of issues. First, the technological and infrastructural developments are not clear at this moment, because these partly depend on different market participants, such as industry and governments. Hence, important issues related to charging times, charging speed, charging locations, maximum range and fuel prices are uncertain for drivers. At the same time, with favorable infrastructure scenarios, many drivers for whom an electric car is inconvenient today may encounter a future in which driving an electric car will be a realistic alternative. Moreover, consumers' uncertainty concerning a vehicle's functional characteristics, such as performance, costs, and return-on-investment of electric vehicles, will decrease over time when more people adopt electric cars and share their experiences.

Second, for many car drivers, the social meaning of a car plays a relevant role in their decision making. Conformity plays an important role in processes of diffusion (Rogers, 2003) and increases at each phase of diffusion. Hence a driver who rejects an electric car at the early introduction stage because an innovative product is a minority choice, may in the future be confronted with a situation in which several friends already adopted an electric vehicle, which will force him or her to consider adoption as well.

In a diffusion process featuring technological and financial developments and a possibly changing social context, non-linear developments may happen. This complexity arises from many interactions on the micro-level (social influence), which cause macro-phenomena to emerge (markets), which in turn affect micro-behavior (choice behavior). Such non-linear developments are hard to derive from cross-sectional survey data. In particular, because there is a vast array of possible policies and technological developments, it is not feasible to collect survey data by confronting respondents with a large number of possible future policy and technology scenarios and by asking them about their future behavior.

Nevertheless, it is important to make an empirically sound estimation of future developments and it would be helpful to have the possibility to explore the impact of different combinations of policy scenarios and market developments on the diffusion process. The methodology of social simulation, as discussed in the introduction of this special issue, is particularly suitable to explore these developments (see *inter alia* Filatova, 2009 and Gnann & Plötz, 2015). Having a valid simulation of the domain of the diffusion of electric vehicles not only contributes to a better understanding of changes in the fuel

systems of cars and the policies affecting these, but also allows to develop dynamic scenarios of how the distribution of different fuel systems will develop in the car fleet.

A social simulation model of this domain requires the representation of needs and decision making of a heterogeneous population of consumers. The Consumat framework (Jager, 2000, Jager & Janssen, 2012) has been developed as a conceptual architecture for developing domain-specific social simulation models that are psychologically plausible. In the current paper, the Consumat approach has been used to develop “STECCAR¹” (*Simulating the Transition to Electric Cars using the Consumat Agent Rationale*), a social simulation model aimed at modelling the dynamics of the car market in the process of moving from combustion to electric engines. STECCAR aims to model consumers in a more psychological way than models based on expected utility maximization (see e.g. the models of the diffusion of electric vehicles described in Zhang et al., 2011 and Gnann et al., 2015).

The purpose of this paper is to present a model that integrates complex behavioral rules in a multidisciplinary modeling context. The presented model is meant to contribute to our understanding of how non-linearities in the market may evolve together with individual preferences for a new vehicle technology under various policy conditions. It will help us simulate a diffusion process of EVs in the Netherlands, explore the role of selected policy measures and their combinations in this process, and explore the effect of two policy regimes on the diffusion of PHEVs and BEVs.

The paper is organised as follows: Section 2 presents the general model and Section 3 describes the model attuned for the analysis of vehicle diffusion. Sections 4, 5 and 6 describe the parameterization, calibration and validation of the model. Section 6 presents the simulation of a default scenario. Sections 7 and 8 present model results on a few single and combined policies, respectively. Section 9 presents conclusions and suggestions for future research.

2: The Consumat model

Consumers display different decision strategies in selecting behavior, such as relying on habits, imitating peers or role-models, making deliberate comparisons, and asking friends for advice. The Consumat model offers a generic conceptual framework that combines and connects these different decision strategies and their underlying drives. Moreover, people’s switching between different decision strategies, for example, when a short period of deliberation results in a change of habit, is explicitly targeted by the Consumat model. The aim of the Consumat approach is to support the development of domain-specific social simulation models of consumer behavior. The rationale of the Consumat approach resides in connecting individual (micro-level) behavioural goals (needs) and experienced uncertainty as drivers of cognitive processes of decision making and memory access. Applied to a population of heterogeneous simulated agents, this results in population behaviour (consumption of

¹ An additional reason for choosing the name STECCAR is its close resemblance to the Dutch word for power plug: ‘stekker’.

opportunities) that aggregates into macro-level outcomes, both in terms of the human environment (e.g., consumptive culture and norms) and the natural environment (e.g., emissions). The Consumat model “closes the loop” by feed-forwarding this aggregated population behaviour towards the decisional context of individual agents at the next moment in time. This allows for modelling individual processes over time, such as habit formation, as well as micro-macro processes, such as the emergence of norms. It also allows for individual agents to switch between cognitive processes when they experience (un)certainty and/or (dis)satisfaction. Figure 1 displays the structure of the Consumat model.

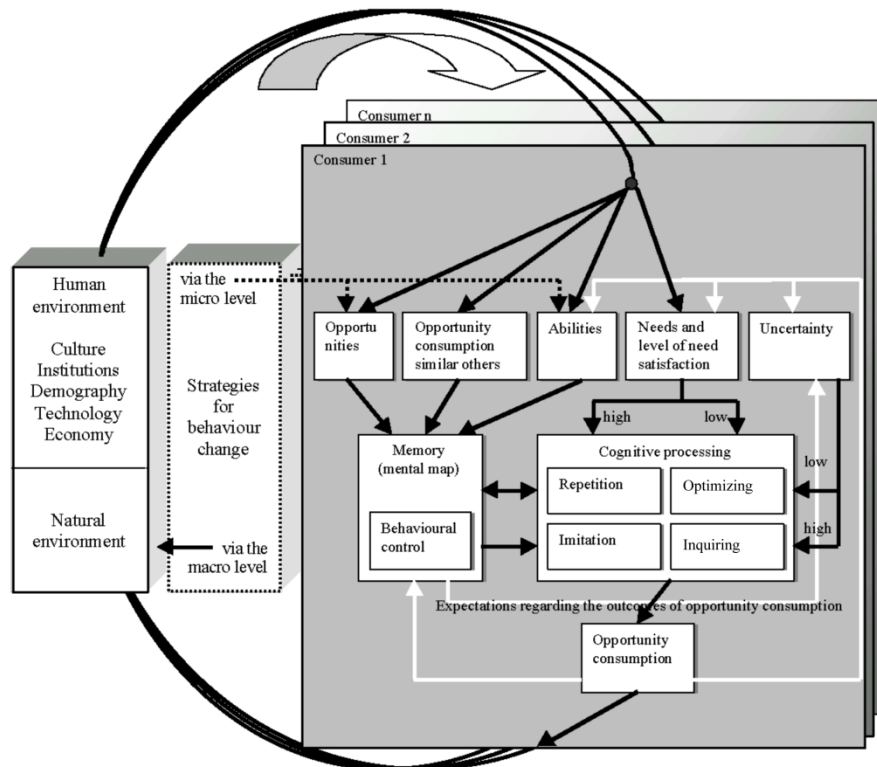


Figure 1: Overview of the Consumat framework

Whereas many sophisticated theories have been developed addressing various aspects of human behavior, the Consumat approach mainly focuses on providing a framework for positioning theoretical mechanisms in a causal loop that is required for formal modelling. The precise implementation of a formal model will depend on the data to be included in the simulation model. In the following paragraphs, we will explain the basic principles of the Consumat approach.

The basic drivers of behavior in the Consumat framework are *needs*; the fulfillment of needs results in *satisfaction*. The needs can be satisfied by consuming certain opportunities, e.g., the purchase of products or the harvest from natural resources. Many theories address the existence of different needs, such as Maslow (1954), Max-Neef (1992) and Kenrick, Giskevicius, Neuberg & Schaller (2010). Nussbaum and Sen (2004) address capabilities instead of needs,

and self-regulation theory addresses more short-term impulses driving behavior (e.g., Baumeister & Vohs, 2007). While we acknowledge the possibility of including more elaborated needs or goals in a model, in the interest of keeping our model transparent we start with three behavior-driving forces: 1) *existence/sustenance*; 2) *social belonging and status*; and 3) *personal preferences*. This also aligns with the three leading behavioral motives of Goal Frame Theory (Lindenberg & Steg, 2007), namely the hedonic, gain, and normative goal frames.

Existence relates to having means of existence, food, income, housing and the like. Agents act in order to avoid depletion of these resources over time. *Social belonging and status* relates to having interactions with others, belonging to a group, and having a social status. *Personal preferences* relates to satisfying one's personal taste with respect to overall life values and norms, such as environmental protection, altruism, or enjoyment of life. Agents balance the importance of these needs, so that some agents may be mostly motivated by the drive to manage their resources (existential need), while others may be more susceptible to the influences of other agents (social need). These needs are all relevant with respect to the need-satisfying capacities of *behavioral options* available to agents to satisfy their needs.

To perform behavior, an agent possesses *abilities* (or capacities), which relate to its capacity to actually use particular behavioral options. Hence, abilities address the exchange between the demands of a behavioral opportunity to be implemented, and the related capacities of the Consumat, such as income, cognitive capacity, a piece of land, tools, et cetera. Agents have a memory for behavioral opportunities and other agents' behavior and abilities, which is only updated if cognitively demanding decision strategies are being used.

Decision making is an important element of the Consumat approach (Jager, 2000). Human decision making is an extensive and rich research field, and a review falls beyond the scope of this paper (but see e.g. Gigerenzer, Hertwig, & Pachur 2011). The Consumat approach aims to provide a simple structure for simulated consumers to determine which type of decision strategy is used under which conditions. For this, we use a simplistic distinction between decision strategies on the basis of the cognitive effort involved and the social versus individual orientation of the process.

Uncertainty and need satisfaction drive the type of decision making in which an agent engages (see Jager, 2000 for an extensive description). A high degree of satisfaction suggests that the agent has made good choices before and that it is doing well, so there is no urge to engage in extensive decision making right at that moment. Dissatisfaction, however, requires extensive scrutiny of alternatives to increase the agent's satisfaction. Uncertainty is a psychological state influenced by insecurity concerning the expected results of performing (new) behavior, e.g., in situations where many alternatives are available and choice options are composed of many attributes. Also when one's behavior deviates from the norm, uncertainty may arise. Using the experiences of other people and observing their behavior is an effective strategy in these circumstances. Theory on similarity shows that people have a stronger tendency to interact with similar others (see e.g., Byrne, 1961, McPherson et al., 2001); correspondingly, in the Consumat framework the chances of interaction can be

based on similarity concerning agent characteristics and behavior. On the basis of similarity, a fixed social network can be constructed, but because the properties of agents may change over time, this similarity can be recalculated at certain time intervals. This allows for simulating a dynamic network, which may be relevant in studying the development of consumer segments over time. Both fixed and dynamic networks can be implemented using this approach. Depending on the satisfaction and uncertainty levels of the Consumat agent, it will engage in one of the four cognitive strategies illustrated in Figure 1, in the part of Consumer 1 labeled 'Cognitive processing'.

In case of low uncertainty and high satisfaction, agents engage in *repetition*, which is the script-based mechanism driving habitual behavior (e.g., Wood & Ruenger, 2016). A high uncertainty combined with high satisfaction results in *imitation* (e.g., Bandura, 1962). When satisfaction is low, the agents are more motivated to invest effort in improving their situation. Hence when they are certain but dissatisfied, they will engage in *deliberation*, which is an assessment of available options and is implemented as expected utility maximization (see e.g. Anand, 1993). Dissatisfaction combined with uncertainty results in *inquiring*, where the behavior of comparable others is evaluated and copied if it increases expected satisfaction (see e.g. Ellison & Fudenberg, 1995). Social decision making is usually directed at similar others (e.g., Rosenbaum, 1986), where similarity is related to abilities.

The agents have a memory that serves as a mental map. Direct experiences with behavior as well as information obtained from deliberation and inquiring will be stored in memory and used in future decision situations. Hence, the memory is updated only when the agent engages in deliberation or inquiring. As a consequence, a satisfied agent can continue to habitually perform particular behavior (repetition) without updating its memory with information on newer and potentially better opportunities such as better performing electric cars. Combining information on its own capacities and the requirements for using a certain behavioral opportunity results in the formalisation of behavioral control in the memory, e.g., the agent knowing whether it can financially afford a certain product.

The behavior of individual agents aggregates into collective impacts on the human and/or natural environment, depending on the domain being modelled. For example, if many agents follow a certain fishing strategy, this will impact the market price of fish (economy) and fish-stock (ecology, see e.g. Jager *et al.*, 2000)

The Consumat provides a generic framework that can be applied to different domains of environmentally relevant behavior, e.g. consumer life styles (Bravo, Vallino, Cerutti, Pairotti, 2013), farmers' interaction with climatic change (Van Duinen, Filatova, Jager and Van der Veen, 2015), and integrated models of consumer behavior, economic markets and ecological systems (Jager, Janssen, De Vries, De Greef and Vlek 2000). Depending on the domain and the available data, the Consumat approach can guide the development of a specific social simulation model. In the following sections, we will explain how the STECCAR model, which is based on the Consumat approach, has been developed using a large dataset of questionnaire responses of Dutch automobile drivers.

3: The STECCAR model

The STECCAR model is aimed at capturing the decision making of car drivers concerning the type of car they plan to purchase: fuel, PHEV or BEV. A Java based implementation of the model was created using the Repast Symphony 2.1 agent-based modeling toolkit and is available in the openABM model library. This section provides a short description of the main components of the STECCAR model. Whereas it is common practice to present an ODD protocol to explain the precise operation of a model in social simulation literature (see e.g. Grimm *et al*, 2005), due to the length and detail of such a protocol we refer the reader to Kangur (2014) for a full technical description of the model.

The model has been parameterized using a dataset that was collected in a research project on driving behavior and preferences. The data comes from a large-scale national internet-based questionnaire that was conducted among Dutch car drivers drawn from a commercial panel (Panel Inzicht, www.panelinzicht.nl). The survey was administered in June 2012 and the data includes individual characteristics of the respondents, their current vehicle, and their driving behavior, as well as perceptions and evaluations of various attributes of full electric cars, attitudes towards full electric technology, the likelihood of adopting a full electric car, and the adopter type regarding innovative cars. The sample (N = 2,977) was randomly drawn and stratified according to gender, age, income and education. It is fairly representative of general Dutch adult population (CBS, 2011) and of driver license holders (BOVAG-RAI, 2012). The mean age of participants was 47 (SD = 14.0); 50% was male. This dataset includes both car lessees (4%) and owners (96%), out of which 24% were going to buy a new car and 76% were going to buy a used car. This enables us to model market developments both on the primary market (new cars) and on the secondary market (used cars).

The core of the STECCAR model is a set of agents that each own a personal vehicle to satisfy their needs. Whereas the Consumat model traditionally defines three types of needs - subsistence, social, and personal preferences - the STECCAR model incorporates four needs: financial, functional, social, and environmental. The first two needs jointly encompass subsistence, but due to their distinct nature and the structure of the dataset, they are kept separate. While the financial need straightforwardly defines an agent's wish to have sufficient affluence, the functionality need relates to the functional reason for owning a car: to travel desired distances. The social need is implemented as described in the Consumat model and encompasses belonging and status. Finally, the environmental need represents the agent's personal preference to lower its negative impact on its environment in terms of pollution.

Vehicles using different fuel technologies exist within the agents' world: traditional gasoline cars, full battery electric vehicles, and plug-in hybrid electric vehicles. Agents are restricted in their behavior by the amount of money they have and their ability to refuel cars that use alternative fuel technologies.

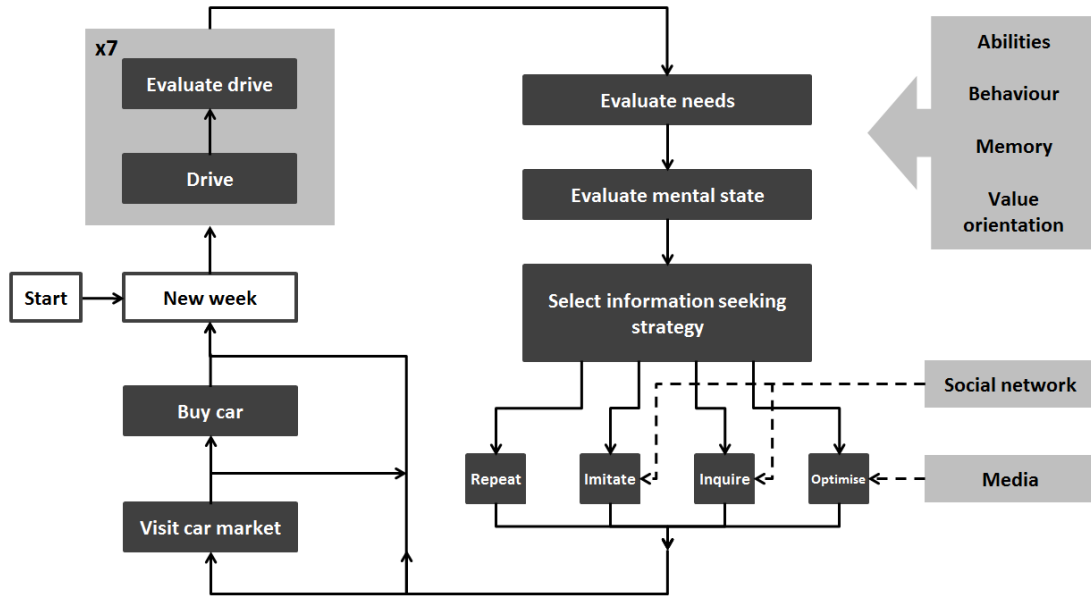


Figure 2: Overview of the STECCAR model

Figure 2 provides a visual overview of the STECCAR model. Each cycle of the simulation represents one week in the agent's world. Therefore, at the start of each cycle, each agent has seven opportunities to travel a daily distance with its personal vehicle (grey box in the top left corner). During a drive, the vehicle will need refueling when it runs out of energy and failures may occur which lead to maintenance costs. After each trip, the agent decides how satisfied it is with its vehicle's costs and functionality and updates its knowledge about its current vehicle.

At the end of the week, the agent makes a comprehensive evaluation of how its current vehicle influences each of its four needs. The agent focuses on its finances and the functionality of its car, but also aims to optimize its social and environmental needs. This evaluation is combined with personal characteristics that determine how easily the agent is satisfied and how much uncertainty the agent can handle before perceiving itself as uncertain. The result is the agent's mental state, which indicates whether the agent perceives itself as satisfied and certain.

Depending on its mental state, the agent decides whether to engage in an information-seeking strategy to possibly increase its knowledge of other vehicles on the market. A satisfied and certain agent will repeat its current behavior without seeking new information. When an agent is certain but dissatisfied about its current car, it will optimize its knowledge on all available car models using information retrieved from the media. When an agent is satisfied but uncertain, it will imitate the information that other agents in its network know about their current vehicle. This communication with other agents is regulated through a fixed network, which is based on similarity. This similarity encompasses geographical location, income, values, ambition, behavioral preferences, and age. As a consequence, this relatively simple imitation strategy may still result in finding a satisfactory car, because other agents may have optimized their car choice given rather similar conditions.

Finally, an uncertain and dissatisfied agent will inquire into both vehicles owned and not owned by similar other agents.

Both from its personal experience with different vehicles and from information obtained through similar other agents and the media, the agent estimates which vehicle will best satisfy its four needs when it is time to purchase or lease a new vehicle. This situation occurs when the agent is repetitively unsatisfied with its current vehicle, when its vehicle's maintenance costs surpass the vehicle's market value, or when the lease contract has ended.

4: Parameterization

Because the parameterization of each single variable implies many augmented choices and functions to translate empirical data into the simulation model, within the context of this paper there is no space to provide the details of this parameterization process. For a full description and operationalization, we therefore refer to Kangur (2014). Here we provide a listing of the variables, ordered in the main concepts of the agents, the vehicles and the infrastructure. Note that for each individual agent, a unique profile is created using the empirical data.

4.1: Agents

From the original dataset, only the 1,795 respondents that supplied complete and consistent data, and drove a vehicle that utilized gasoline and/or electricity, were selected. On the basis of this data, the 1,795 agents are equipped with demographics, personal characteristics, driving behavior, vehicle preferences, an initial car, and other variables.

Demographics: each agent has an age, postal code, yearly income, and yearly income tax to be paid. Whereas the model is not explicitly spatial, a spatial proximity between the agents is based on postal-code information.

Value orientation: agents weigh their needs; their social need may focus more on conformity or on anti-conformity; they have an ambition level and an uncertainty tolerance.

Network: Agents have 15 contacts that have been selected on the basis of a weighted combination of similarity on spatial proximity, income, values (relative importance of needs), ambition level, driving pattern and age. Relations are not necessarily symmetrical, which means that it is possible that agent A contacts agent B, while B does not contact A. When there is contact during imitation or inquiring, information is exchanged between both agents.

Driving behavior: agents have a yearly mileage, an individual frequency with which specific distances are driven, work trips, a preferred refuel moment (e.g., when the tank is half full), and access to home charge.

Vehicle preferences: agents have an ownership type (private or lease), a vehicle price class, a minimum driving range required, a maximum accepted charge time, a maximum charge time distance and maximum accepted carbon emissions.

Initial vehicle: agents start in the simulation with their initial vehicle having an age, mileage, ownership duration, fuel technology, and car model.

Other: agents also want to spend a certain proportion of their income towards a vehicle; in their social network they have friends driving certain cars and a level of expertise on electrical vehicles.

4.2: Vehicles

There are three different fuel types available in the simulation; for each fuel type, different car models exist, each with different financial and emission characteristics. Characteristics that are not particularly distinctive for fuel types (such as car size, or having airbags and such) are left out.

Car models: Variations of three basic cars are modeled, namely battery electric vehicles (BEV), plug-in hybrid electric vehicles (PHEV)², and gasoline vehicles.

General aspects: new cars are introduced on the market; cars have a depreciation value, a certain fuel economy, and a certain price per kWh; lease cars also have a length of the contract.

4.3: Infrastructure

Three types of infrastructure are discerned: the car market, refuel stations and taxes.

Car market: the car market starts with an empirically based set of available used cars with a certain age and mileage.

Refuel stations: especially for electric vehicles, the following changeable settings are relevant: access to home charge, access to work charge, probability of road charge, refuel time, refuel costs, and maximum recharge capacity.

Taxes: Two taxation regimes are included in the model. Company car tax is an income tax to be paid by lessees because the lease car is considered to be a part of one's taxable income; its height depends on the purchase value of the lease car and its emissions. Road tax is a generic taxation for vehicle car owners based on weight and fuel type of their car.

4.4: Media

The media provide information about new cars that can be used by the agents in their decision-making process. The information shared by the media may be more or less correct. The media publish vehicle information with a random deviation between 0 and 30% from the vehicle's true characteristics.

5: Calibration

Nearly all of the parameters mentioned in the previous section were initialised using either the dataset from Bockarjova & Steg (2014), or using other empirical reports. Only a handful of parameters were left open, and thereby used to calibrate the model and fine tune its performance to real world data. These parameters included: the agent's satisfaction threshold, i.e. how often should an agent be unsatisfied until it considers purchasing a new vehicle; the influence of planned trips that cannot be made with a BEV on an agent's satisfaction level;

² We note that during the collection of data (June 2012), we did not make a distinction between conventional hybrids and plug-in hybrids, because this would unnecessarily complicate the questionnaire, which focused mainly on BEVs. However, we feel that it is possible to interpret the data in the light of PHEVs, given their wide adoption by Dutch drivers up to now.

and the amount of vehicles on the used car market that are ‘exported’ each year. All three parameters influence purchase behaviour and the stability of the car market. A parameter search was performed to explore settings which best matched the patterns of real world data in previous two years (see also Section 6). Like with the empirically initialised parameters, the actual values are discussed in Kangur (2014).

6: Validation

The survey data through which the agents were initialized was collected in June 2012, two years before STECCAR was developed. Therefore, the first part of the default scenario spans the course of this same time frame: July 2012 until July 2014. Fifty initial test runs showed that the coefficient of variation of the simulation’s diffusion process stabilizes after thirty runs, and hence we decided that thirty simulation runs would be sufficient to have a representative sample. By tailoring a scenario that represents the actual developments in the most recent two years, the simulation’s emerging macro-level results can be compared to recent real-world patterns, as is common within the pattern modelling validation strategy (Grimm et al., 2005). In Table 1, we present the cars that were introduced in the market and that were introduced in the model for validation purposes.

Table 1: Specifications of all car models introduced during the model validation

Week	Fuel	Model	Price in €	Gasoline range (km)	Capacity (kWh)	gCO ₂ /km
50	BEV	S85	85000		80	0
54	BEV	FOCUS	39500		30	0
60	PHEV	V60	64500	1100	8	49
72	BEV	EGOLF	34500		30	0
78	BEV	LEAF	29500		30	0
90	PHEV	VOLT2	39500	550	11	27

Validation of emerging patterns is done within four themes: market stability, ownership aspects, scrappage characteristics, and diffusion of electric vehicles.

6.1: Market stability

Stability of the car market is crucial for a realistic representation of the diffusion of new vehicles. If there are insufficiently many cars on the secondary market, too many dissatisfied agents will continue driving their current vehicle even when they have the resources to purchase a more satisfying one. If there are too many used vehicles available, new cars will lose in relative value over time without being driven, leaving buyers on the secondary market with exceptionally attractive cars to choose from.

Converting the annual car sales in the Netherlands (CBS, 2014) to the simulation’s population, approximately 100 new cars and 400 used cars should be sold each year. Thirty runs of the default scenario show average sales of 53 and 69 new cars in the first and second year respectively. For used cars, annual sale numbers are 346 and 396 during the first two years. Running STECCAR for

11 additional years resulted in a sales figure of approximately 110 new and 405 used cars a year, hence both sale figures remain close to their appropriate values.

6.2: Ownership aspects

Important variables related to ownership are ownership duration and vehicle age. Dutch vehicle ownership duration - the period of time that a car is owned before being resold - has steadily increased from 3.6 years in 2010 to 3.85 years in 2013 (VWE, 2014). An increasing duration trend is also seen in the default scenario, where average ownership duration increases from 3.5 to 4 years after two years. The average age was 7 years in 2000; it has increased to 9.1 years in 2013. In the default run, the average age starts off at 8.25 years and reaches 9 years by the end of year two.

6.3 Scrappage characteristics

According to Statistics Netherlands, 219,836 personal vehicles were scrapped in 2013 (CBS, 2014). Converted to the car fleet size in STECCAR, this entails that roughly 50 vehicles should be scrapped each year. Results are consistently around 65 scrapped vehicles per year. In 2012, the average age of scrapped vehicles in the Netherlands was 17 years. In the default run, the age of scrapped vehicles starts off somewhat lower at 15.5 years but grows after a few years and then stays between 16.5 and 17.5 years, close to the real-world data.

6.4: Diffusion of electric vehicles.

Due to the small volume of electric vehicles currently registered in the Netherlands, and the even smaller sample of agents in the simulation, validating the diffusion of electric cars is difficult. A trend that is clearly observed in the Netherlands, however, is a greater consumer interest in plug-in hybrids than in fully electric cars. At the end of June 2014, 0.064% of the cars on the road in the Netherlands were a BEV and 0.4% were a PHEV. The validation results are somewhat higher, at 0.24% and 0.85%, respectively. This entails that the tendency to purchase a PHEV in favor of a BEV is observed in the simulation's behavior, but that it is unfounded to put predictive value on the absolute diffusion magnitude and time line.

6.5: Conclusions about the parameterization of STECCAR

The previous subsections show that the parameterization of the STECCAR model results in a simulation that is capable of following the empirical trends of several variables. Obviously, this exercise only refers to two years of observed data in which no substantial take-off of BEVs and PHEVs took place. If the proportion of electric vehicles were to increase further, more social interaction would take place and more experiences would be shared. As a result, the process would be expected to behave in a more non-linear manner (see also Rogers, 2003).

7: The default scenario

A sheerly infinite number of policy scenarios can in principle be tested using the STECCAR model in order to find most favorable outcomes. Variations can be made in the type of policies being developed, their magnitude of enforcement

(e.g. taxation, infrastructure development) and their timing. However, this will not be a fruitful exercise since the future holds enormous uncertainties concerning e.g., oil prices, development of hydrogen infrastructure, and autonomously driving cars in sharing systems. Rather than making forecasts of the future, social simulation models can, among other things, reveal the susceptibility of a system to different policy strategies. In this section, we will briefly present the default run of the simulation, in which no additional policy is implemented. This will serve as a base-rate scenario against which to evaluate a number of policy strategies as presented in Section 8. In Section 9, a run in which an ensemble of different policies are jointly introduced is discussed, because combining different policies may result in additional benefits.

7.1: Outline

The default scenario is the continuation of the validation run presented in Section 6. It consists of hypothetical developments over 13 years (676 weeks), from July 2012 up to July 2025. Running this model for 30 times over a longer interval provides insight into the stability of the simulation's behavior. The following assumptions have been made for the default scenario.

New cars entering the market

Table 2 presents the plausible but mostly hypothetical EV car models that are introduced in the market.

Table 2: Specifications of all EV car models introduced during the default scenario.

Week	Fuel	Model	Price in €	Gasoline range (km)	Capacity (kWh)	gCO ₂ /km
130	PHEV	CMAX	34500	850	6	46
145	BEV	OHM	44500		32	0
156	BEV	JOULE	49500		32	0
260	PHEV	FARADAY	29500	700	8	38
390	BEV	HERTZ	24500		30	0
434	PHEV	COULOMB	24500	700	8	32
530	BEV	WEBER	19500		30	0
610	PHEV	HENRY	19500	700	8	28

It is assumed that the remaining high-end price classes will be saturated in the upcoming years with car models similar in range to the currently available cars in the medium range price classes (OHM and JOULE). All subsequent models are introduced at a moment when battery prices are expected to have decreased enough to make their production economically feasible (Kangur, 2014).

To simplify the process of introducing improved vehicles to the new market, car models are replaced annually by an updated model. BEV and PHEV models are replaced by models with an increased battery capacity, depending on how much the battery costs have dropped. In the default scenario, the price per kWh of batteries steadily decreases from € 500 to € 300 between July 2014 and the end of the scenario.

PHEVs and gasoline models are replaced by models with carbon emissions that are 7% lower, but that are equal in all other aspects. This

represents the trend that since 2008, the average carbon emissions of newly registered vehicles in the Netherlands has decreased by 7% annually (CBS et al., 2014). Because this trend will presumably not continue indefinitely, gasoline car emissions reduce only 2% each year after July 2016.

Purchase power

The amount of money agents can spend on maintenance and saving towards a new car steadily increases from 5% of their current household income in July 2014, to 10% at the end of the scenario. Notice that the implicit assumption is made that household income will rise due to economic growth, enabling agents to spend more money on personal items.

Service stations and prices

The probability of encountering a fast charging service station during a trip steadily increases from 0% in July 2014 to 95% at the end of the scenario. During the same time period, the proportion of agents with access to home and work chargers increases to 80% and 60%, respectively. At the moment that fast charging stations along the highways start occurring (July 2014), the price of fast charging per kWh increases to € 0.15/km, or € 0.75/kWh for EVs with a fuel economy of 20 kWh/100 km. This reflects the high costs that recently built fast charging stations in the Netherlands charge their consumers (Fastned, 2014). Starting from July 2015, the fast charge price steadily decreases again to € 0.09/km at the end of the scenario. The price of gasoline increases between July 2014 and the end of the simulation to € 0.15/km, which would equal € 2.50/litre for vehicles with a fuel economy of 6 litres/100km.

Taxation

All personally owned vehicles with carbon emissions lower than 50 g/km are exempt from road taxes in the Netherlands until January 2016. Therefore in the default scenario, all car models with carbon emissions lower than 50 g/km are tax free during the first three-and-a-half years, while all other models come with a monthly tax of €50³. Road taxes are expected to be less favorable for EVs after this date, which is translated into a monthly tax of €25 for vehicles with emissions lower than 50 gCO₂/km and €50 for all other car models in the simulation, starting January 2016. Lessees pay a company car tax instead of general road taxes. In the Netherlands, all vehicles with carbon emissions lower than 50 gCO₂/km were exempt from company car taxation until January 2014. Since then, all EVs have been taxed, but taxation has been directly related to carbon emissions. This results in zero-emissions vehicles having the lowest available company car tax on the market.

7.2: Results

In Figure 3, the average diffusion of PHEVs and EVs can be seen for thirty runs.

³ The tax levels in the simulation are on the low side compared with reality.

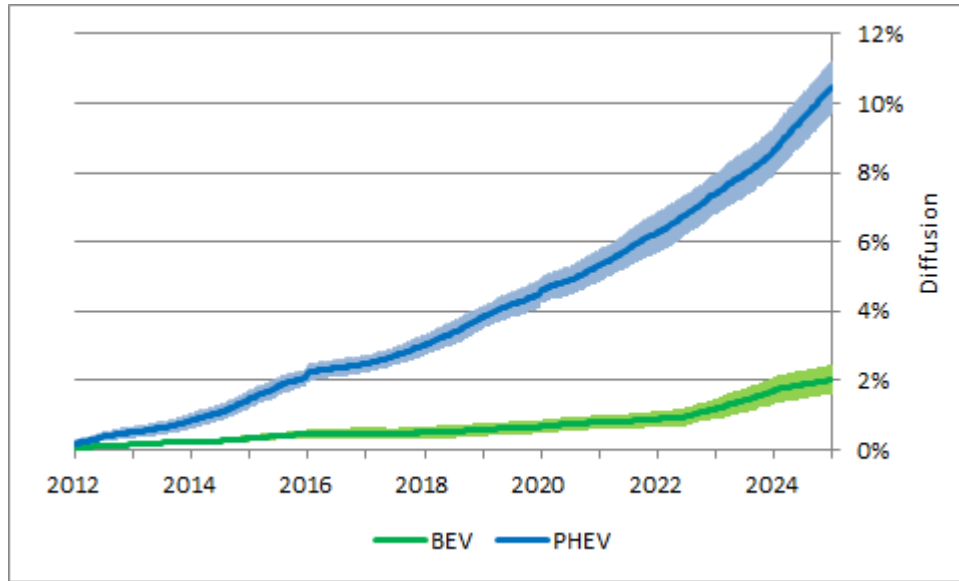


Figure 3: Diffusion of PHEVs and BEVs in the default scenario. The solid line represents the average diffusion over thirty runs; the lighter area represents the standard deviation at each moment.

These results indicate that the default scenario will not result in a large market share of PHEVs and BEVs. In 10 years' time, the market share for PHEVs is 10.45%, while the share of BEVs will be only 2.03%. Cheah and Haywood (2011) indicate that a PHEV (plug-in) uses 72% less fuel than a conventional gasoline car. In the default scenario this would result in a total emission reduction lower than 10%, which in practice may be even lower as it is suggested that many PHEV owners do not consistently charge their car (Visscher, 2014). In Figure 4, the satisfaction of the population with the different types of cars is presented for the default scenario.

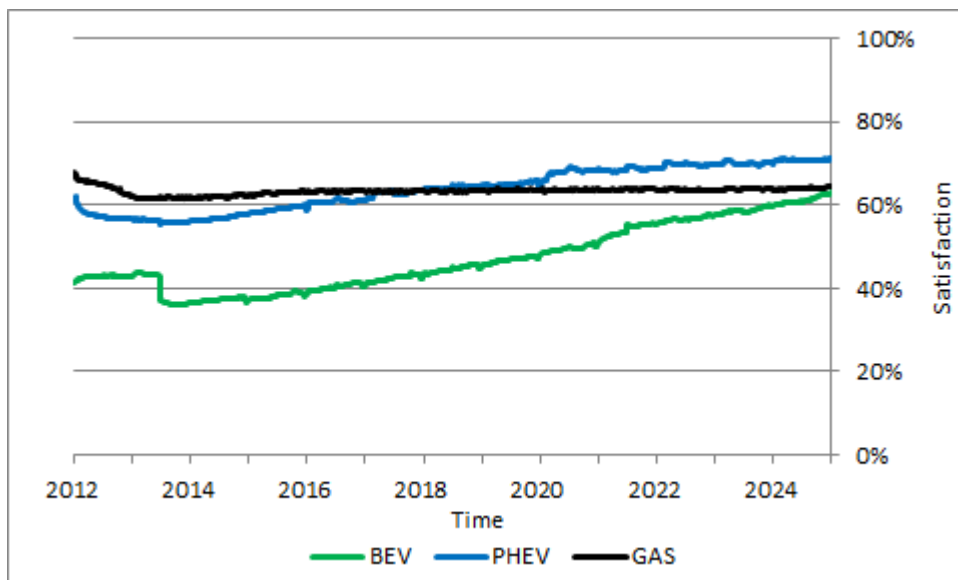


Figure 4: Satisfaction of the population with the different types of cars in the default scenario over thirty runs.

Figure 4 shows that at the start of 2014, a drop occurs in the satisfaction with BEVs, which is a direct consequence of imposing a positive company car tax for low carbon emission vehicles. Interestingly, this policy change does not influence the satisfaction with PHEVs, indicating that other motives keep PHEVs sufficiently attractive even at higher financial costs.

While changes in company car tax policy have a direct effect on the average perceived attractiveness of electric vehicles, the abolishment of road tax exemption for low carbon emission vehicles at the beginning of 2016 causes no such response. Because most agents who can afford an electric vehicle are initially lessees, taxes targeted at lessees have far more impact than general road taxes.

As a direct effect of the policy of steadily increasing the number of fast charging service stations in the agents' world, the expected satisfaction with BEVs continuously rises, starting halfway 2014. By 2025, BEVs are on par with gasoline vehicles and are perceived by the agents to be almost as satisfactory as PHEVs.

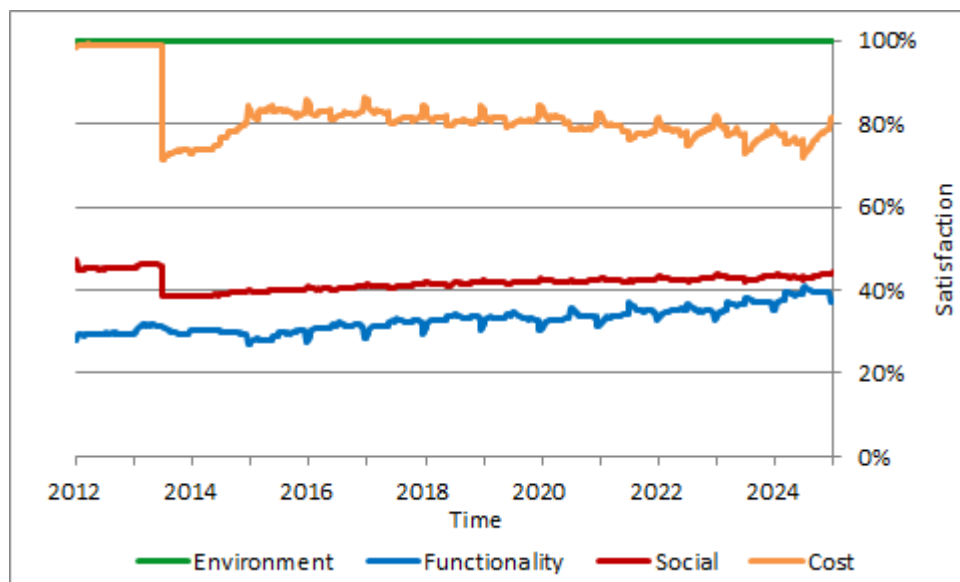


Figure 5: expected average satisfaction with newly available BEVs for different needs over thirty runs: costs (orange), functionality (blue), social (red), environment (green).

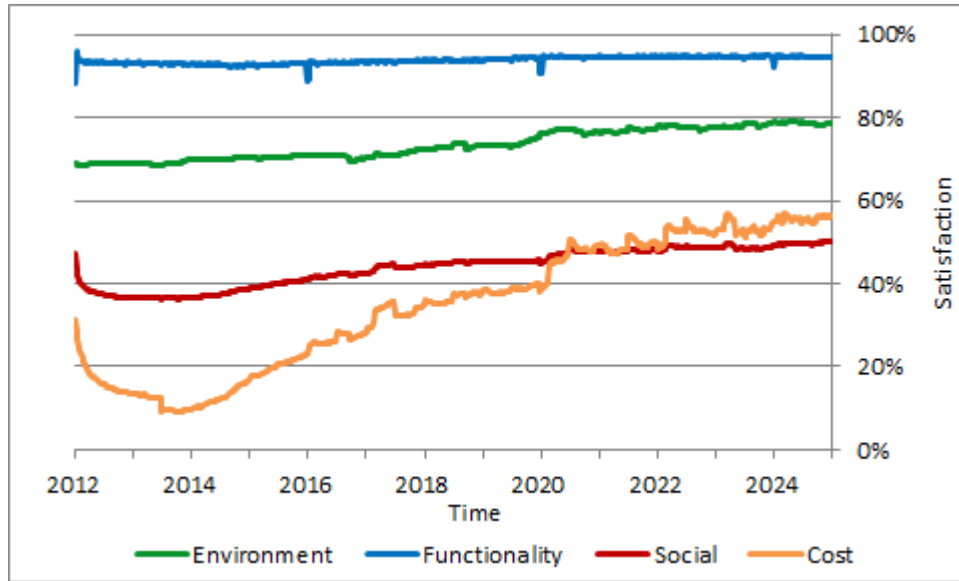


Figure 6: expected average satisfaction with newly available PHEVs for different needs over thirty runs: costs (orange), functionality (blue), social (red), environment (green).

Figure 5 and 6 provide more insight into the composition of the agents' need satisfactions in relation to BEVs and PHEVs, respectively. Both figures show the average satisfaction with vehicles that are currently for sale on the market, broken down by the four different agent needs that were described in Section 3⁴.

Both BEVs and PHEVs do not contribute much to social satisfaction because they remain cars driven by a minority. For the PHEV the environmental satisfaction is quite high, and for the BEV this is maximal. A large contrast exists on the satisfaction with the costs, which is satisfactory for BEV and low for PHEV. On the contrary, functional satisfaction is low for BEVs, due to the low range, and high for PHEVs.

⁴ The annual 'spikes' in Figure 5 coincide with annual updates of the S85. Right after the update, most agents are still unaware of this newer model's existence and therefore their average opinion on all newly available BEVs temporarily does not take this model into account. The spikes in the figure therefore show that without the S85, the agents perceive the average BEV as less functional but more financially attractive. Since this average opinion is only computed for the sake of this figure, this has no further consequences for the simulation. The four year spikes in Figure 6 are caused by lessees whose lease contracts expire and who select a PHEV as their new vehicle. Right after their purchase, they do not have any functional experience with this vehicle yet, causing the average functional satisfaction to go down.

Table 3: Owner characteristics per fuel technology at the end of the default scenario.

	Range	BEV	PHEV	Gasoline
Average ambition level	0 - 1	$\mu=0.62$, $\sigma=0.028$	$\mu=0.64$, $\sigma=0.006$	$\mu=0.55$, $\sigma=0.001$
Average uncertainty tolerance	0 - 1	$\mu=0.59$, $\sigma=0.019$	$\mu=0.58$, $\sigma=0.007$	$\mu=0.49$, $\sigma=0.001$
Lessee percentage	0 - 100%	$\mu=44\%$, $\sigma=7.6\%$	$\mu=27\%$, $\sigma=2.6\%$	$\mu=0.32\%$, $\sigma=0.12\%$
Average income category	1 - 10	$\mu=6.9$, $\sigma=0.24$	$\mu=7.2$, $\sigma=0.08$	$\mu=5.0$, $\sigma=0.02$
Average yearly mileage	2,500 km - +50,000 km	$\mu=22,303$ km, $\sigma=2,906$ km	$\mu=23,450$ k m, $\sigma=870$ km	$\mu=13.997$ km, $\sigma=53$ km
Average financial need weight	0 - 100%	$\mu=19.1\%$, $\sigma=0.70\%$	$\mu=19.7\%$, $\sigma=0.19\%$	$\mu=16.8\%$, $\sigma=0.03\%$
Average functional need weight	0 - 100%	$\mu=26.9\%$, $\sigma=0.34\%$	$\mu=27.5\%$, $\sigma=0.17\%$	$\mu=27.6\%$, $\sigma=0.02\%$
Average social need weight	0 - 100%	$\mu=26.3\%$, $\sigma=0.64\%$	$\mu=26.5\%$, $\sigma=0.18\%$	$\mu=28.3\%$, $\sigma=0.02\%$
Average environmental need weight	0 - 100%	$\mu=27.8\%$, $\sigma=0.45\%$	$\mu=26.4\%$, $\sigma=0.17\%$	$\mu=27.2\%$, $\sigma=0.02\%$

Agents who purchase an EV distinguish themselves from gasoline car owners in several ways in the default run of the STECCAR model. Table 3 shows that the average adopters of both BEVs and PHEVs are agents having a higher ambition level and uncertainty tolerance. This implies that they are less likely to imitate the behavior of other agents, and are more likely to individually optimise their choice for a fuel system. With regard to satisfying their needs, Table 3 shows that adopters of EVs on average place slightly more importance on their financial need and slightly less importance on their social need than gasoline car owners do. This indicates that agents adopting an EV evaluate a car a bit more on personal financial aspects and less on conforming to other agents' behavior. This further contributes to the more individualistic orientation of the innovative agents. Concerning ownership, Table 3 shows that adopters of EVs are more often lessees than gasoline drivers are. Additionally, they have a higher income and drive more kilometres on a yearly basis than gasoline drivers. The question thus arises which policy measures can be developed to stimulate a potentially interested group of agents to switch towards PHEVs and BEVs.

8: Single policies

In order to reduce CO₂ emissions, different policies have been suggested in policy debates or implemented by governments. In this section, we will report the results of modelling a selection of single policy measures. We selected financial and technical policies where public policy can have an impact. In Kangur (2014), more single policy measures are presented.

8.1: Company car tax exemption: zero tax

Two scenarios were developed to inspect the effect of abolishing the company car tax for low carbon emission vehicles. In the *company car tax* scenario, zero company car tax is reinstated for all BEVs and PHEVs. In the *company car tax-BEV* scenario, a policy more strongly in favour of battery electric vehicles is enacted. Here, only zero-emission car models are favoured for zero company car tax.

The average diffusion processes over 30 runs of the scenarios are given in Figure 7. Because the lease market is relatively small, company car tax exemption does not result in an increase of electric vehicle (EV) owners overall. It does, however, influence the competition between PHEVs and BEVs.

The results show that reinstating company car tax exemption for all low emission vehicles results in a very weak preference for BEVs while PHEV adoption slightly decreases. This suggests that company car taxes are especially punitive for BEVs, making PHEVs seem favourable over BEVs. This is in line with the finding in Section 7.2 that the 2014 company car tax increase for all EVs resulted in a sharp decrease in BEV satisfaction, but not in PHEV satisfaction.

The effect of the *company car tax-BEV* scenario is much stronger. When PHEVs are treated less favourably than is currently the case and zero-emission vehicles fall in the zero company car tax again, 94% more BEVs are sold in comparison to the default scenario.

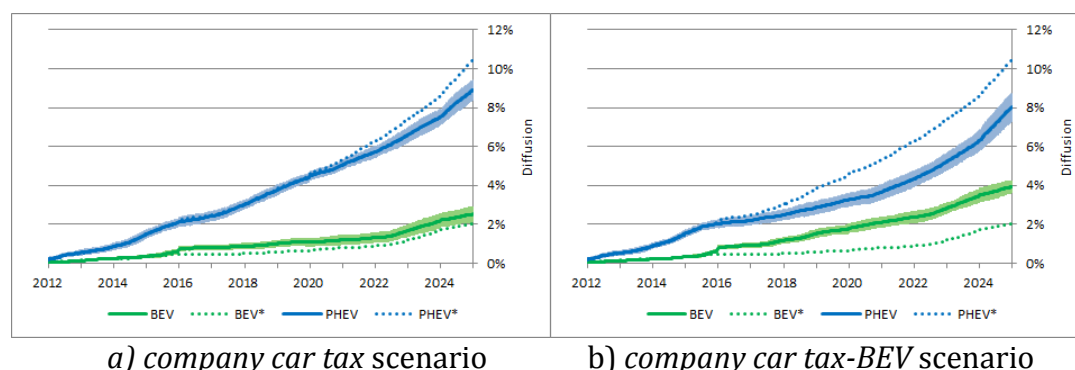


Figure 7: Diffusion of PHEVs and BEVs in the company car tax and company car tax-BEV scenarios, during which zero company car tax was reinstated for low carbon emission and zero-carbon emission vehicles, respectively. The solid line represents the average diffusion over thirty runs; the lighter area represents the standard deviation at each moment. The average diffusion process during the default scenario is added for reference (dotted line).

8.2: Fuel excise duties and subsidies

In scenario *GasCosts*, the excise duties on gasoline are further increased yearly⁵. Starting from July 2015, gasoline prices are instantly raised €0.005/km at the start of each year. This results in a final gasoline price of €0.20/km, or €3.33/litre for cars that have a fuel economy of 6 litres/100km, at the end of the scenario.

⁵ This scenario can also be interpreted as a price rise on fuel, which has been the case in the past decade. Experience shows that prices can be very volatile and can rise even more than currently assumed in the model, or can decrease unexpectedly.

Instead of increasing excise duties on gasoline, the government could also subsidise the price of electricity at fast charging service stations. Scenario *ChargeCosts* is constructed to observe what the effects of this single measure would be. Starting from July 2015, the costs of electricity at fast charging stations is reduced €0.005/km once every year. The final fast charging price is then €0.04/km at the end of the scenario, which coincides with €0.20/kWh when a fuel economy of 20 kWh/100 km is used.

After thirty runs of both scenarios, no observable deviations from the default scenario are found. This suggests that solely increasing gasoline prices or reducing electricity prices does not make driving BEVs or PHEVs significantly more attractive in comparison to driving gasoline vehicles. This could be due to other obstacles that must first be removed, such as limited charging availabilities or unaffordable retail prices of EVs. In Section 9, this hypothesis is further explored by combining the *ChargeCosts* scenario with another policy.

8.3: Purchase subsidies

One limiting factor to a quick diffusion of electric vehicles could be their high initial purchase costs. Since EVs are only available in the higher price classes, they are initially off limits to the largest bulk of consumers who prefer to buy vehicles in the lower price classes. By subsidising the purchase of EVs, the government could allow these alternative fuel technologies to compete in a larger segment of the market at an earlier moment in time.

In the *Subsidies* scenario, the purchase price of all EVs introduced after July 2015 is reduced by €5000. This amount was chosen to ensure that each EV is placed one price class lower than in the default scenario. Two extra car models are introduced to fill in the gaps between price classes which would otherwise arise.

In the *Subsidies-BEV* scenario, a different approach to purchase subsidies is taken. Now, only the BEVs introduced after July 2015 are reduced in price by €5000. All PHEVs have the same purchase price as in the default scenario, and therefore no extra PHEV is introduced.

As Figure 8 shows, the *Subsidies* and *Subsidies-BEV* scenarios have very different effects on the car market and the diffusion of electric vehicles.

The *Subsidies* scenario results in a 48% higher proportion of PHEVs (15.47% in total) on the road at the end of the scenario compared to the default scenario (10.45%). This is a large increase over the previous scenarios. The average final proportion of agents who own a BEV is only slightly higher in this scenario than in the default scenario. These results indicate that when EVs become available in lower price classes, the diffusion trend in the default scenario is strengthened but not altered.

In the *Subsidies-BEV* scenario, the diffusion of PHEVs is not affected by the subsidies that only apply to BEVs. The final proportion of PHEV owners is similar to that in the default scenario. The proportion of agents that own a BEV by the end of the scenario however, has increased by 71%, to 3.47% in total. According to the STECCAR simulations, subsidies can therefore increase the sales in zero-emission vehicles, but this effect is diminished if other low-emission vehicles receive similar benefits.

An interesting finding is that although purchase subsidies are introduced in 2015, their effect does not become noticeable until 2023. At the very least, one would expect that the number of BEV owners would start to increase in 2020, which is the moment when a vehicle becomes available in the €15,000 to €20,000 price class and the diffusion of BEVs takes off in the default scenario. A possible reason for this delay is the slow onset of a reliable network of fast charging service stations and consequently the limited range of BEVs, which initially reduces their estimated satisfaction. A follow-up scenario explores this hypothesis further, by introducing a nation wide fast charge network at a quicker rate.

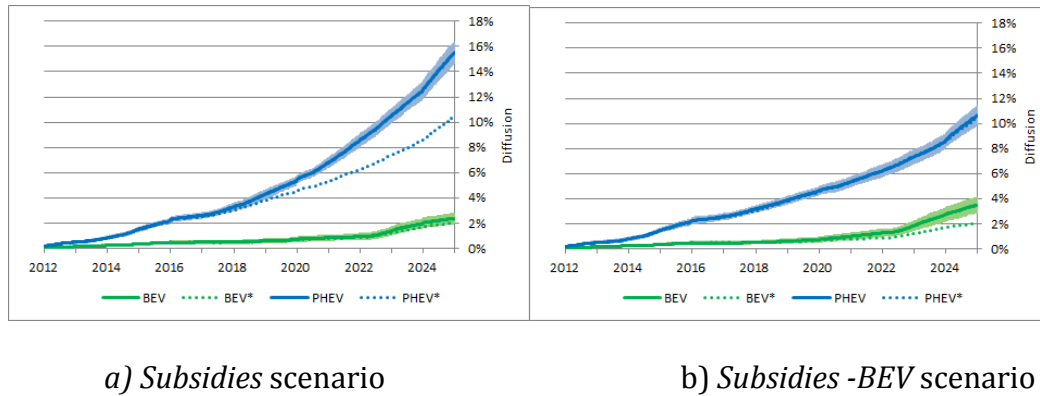


Figure 8: Diffusion of PHEVs and BEVs in the Subsidies and Subsidies-BEV scenarios in which subsidies reduce the purchase price of all EVs or of BEVs only, respectively. The solid line represents the average diffusion over thirty runs, the lighter area represents the standard deviation at each moment. The average diffusion process during the default scenario is added for reference (dotted line).

8.4: Increase in fast charging opportunities

Scenario *FastCharge* was created to investigate the influence of a quick realisation of fast charging infrastructure in the Netherlands. Initial plans aimed at a nation-wide network by 2016. Indeed, 148 stations were realised by May 2016, which averages to one station per 280 km²⁶. Although arguably this does not represent a full national coverage yet, the *FastCharge* scenario was designed to explore the initial plan. Therefore in the *FastCharge* scenario, the probability of encountering fast charging service stations increases to 95% between July 2014 and July 2016.

The average diffusion process over 30 runs of the *FastCharge* scenario is shown in Figure 9. The diffusion of BEVs is positively influenced by a quicker introduction of a nation-wide network of fast charging stations, which becomes noticeable directly after the infrastructure is complete. At the end of the scenario, there are 62% more BEV owners in comparison to the default scenario. The adoption of PHEVs decreases slightly in comparison to the default scenario. However, because the results are so close, it is inconclusive whether this is due to direct competition from BEVs or to chance.

⁶ Results obtained from <http://www.thenewmotion.com> on May 5th 2016.

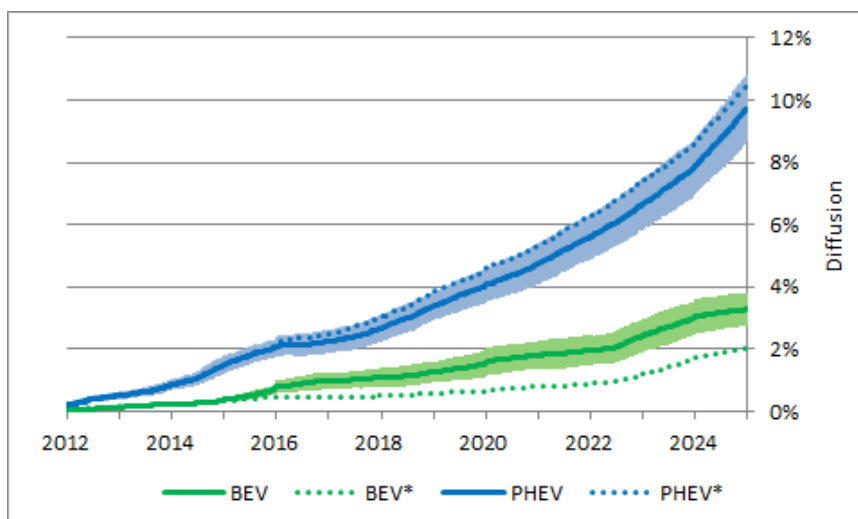


Figure 9: Diffusion of PHEVs and BEVs in the FastCharge scenario, in which the probability of encountering a fast charging service station is more quickly increased. The solid line represents the average diffusion over thirty runs, the lighter area represents the standard deviation at each moment. The average diffusion process during the default scenario is added for reference (dotted line).

9: Combined policies

Previous scenarios showed that the transition to a battery-powered car fleet is a relatively slow process. At the current rate at which owners purchase or lease new vehicles and with the prevailing segment of consumers who prefer used cars over new cars, it would take more than a decade until one out of eight agents owns an EV, even if electric vehicles become within financial reach optimistically soon.

However, it may well be that different policy measures interact and may jointly cause effects that are larger - or smaller - than their individual summed-up effects. A more complex package may even be countereffective. Because policy generally involves the alignment of different policy measures into a more or less coherent package, we expect that this may create conditions for a more rapid diffusion of electric cars.

The scenarios in this section combine the previously explored measures to examine what happens when the initial diffusion of EVs is stimulated by combinations of measures.

9.1: Increase in fast charge opportunities combined with excise duties and subsidies

The exploration of single policy scenarios showed that within the STECCAR model, a quick realization of a nation-covering fast charge network is an important development to make battery electric vehicles (BEVs) more competitive with respect to plug-in hybrid electric vehicles (PHEVs). Other measures, such as slowly reducing electricity costs at fast charging stations or increasing gasoline costs, had no effect when implemented as single measures. A new scenario was constructed to examine whether these ineffective measures

may become effective in a setting where fast charging stations become readily available at a quicker speed. To do so, the *GasCosts*, *ChargeCosts* and *FastCharge* scenarios were simultaneously applied in scenario *CostsAndFastCharge*.

The results of the *CostsAndFastCharge* scenario are shown in Figure 10. The final proportion of BEV owners is 4.89%, which is 142% higher than in the default scenario (2.03%) and almost 50% higher than in the *FastCharge* scenario alone (3.28%). From these results, it seems that making gasoline fuel prices less attractive while making fast charge prices more attractive, has a greater effect when a nation-wide charge network is already in place. Perhaps the low availability of charging options serves as a bottleneck for other potentially influential policies to come into effect. On a very small level, these results show how different adjustments can influence one another and together push the adoption of a new technology forward.

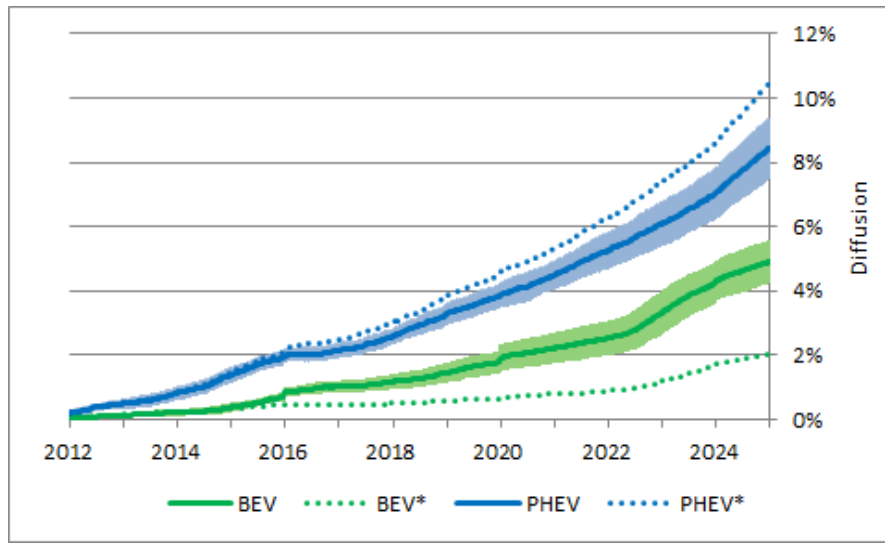


Figure 10: Diffusion of PHEVs and BEVs in the *CostsAndFastCharge* scenario, in which the probability of encountering a fast charging service station is more quickly increased while gasoline prices increase yearly and fast charge electricity prices decrease yearly. The solid line represents the average diffusion over thirty runs, the lighter area represents the standard deviation at each moment. The average diffusion process during the default scenario is added for reference (dotted line).

9.2: Combining all single-policy scenarios

To explore what the diffusion process of EVs might look like under very beneficial circumstances, a scenario was constructed in which all previously mentioned policies are combined. Three additional policies were also added, which are separately examined as single-policy scenarios in Kangur (2014) but were left out of this paper because of length constraints. The first of these policies was a steady decline in the time it takes to fast charge an EV, from 30 minutes during the first two years of the simulation, to 5 minutes at the end of the scenario. This policy by itself did not have an observable effect on EV diffusion. In the second policy, battery prices drop from €500 per kilowatt hour during the first two years of the simulation, to €350 per kilowatt hour at the end. The availability of cheaper batteries affects both the range of vehicles currently

on the market and the moment at which new, cheaper vehicles are introduced. Similarly to the *Subsidies* scenario, this policy mostly stimulated the diffusion of PHEVs. Finally, the last policy abolished ownership taxes for either all electric vehicles, or for BEVs only. This is different from the *company car tax* scenario, which focuses on non-ownership taxes, i.e. those that apply to lessees. Abolishing ownership taxes in isolation did not have any notable effects on the diffusion process.

Two approaches were taken in combining single policies into joint ones. In scenario *MultiPolicy-EV*, each policy is applied in favour of all low-carbon emission vehicles. In scenario *MultiPolicy-BEV only*, a distinction is made between BEVs and PHEVs and policies are applied in favour of BEVs alone. Table 4 provides an overview of all measures included in these two scenarios. Notice that because both governmental purchase subsidies are applied and battery costs drop sharply, by the end of the scenario, EVs are available in price classes twice as low as in the original default scenario.

Table 4: All adjustments made in the MultiPolicy-EV and MultiPolicy-BEV only scenarios, in comparison to the default scenario described in Section 7.1.

Policy	<i>MultiPolicy EV</i>	<i>MultiPolicy-BEV only</i>
Company car tax	Similar to <i>company car tax</i> scenario (Section 7.1)	Similar to <i>company car tax-BEV</i> scenario (Section 7.1)
Fast charge costs	-	Similar to <i>ChargeCosts</i> scenario (Section 7.2)
Gasoline costs	-	Similar to <i>GasCosts</i> scenario (Section 7.2)
Subsidies	Similar to <i>Subsidies</i> scenario (Section 7.3)	Similar to <i>Subsidies-BEV</i> scenario (Section 7.3)
Fast charge probability	Similar to <i>FastCharge</i> scenario (Section 7.4)	Similar to <i>FastCharge</i> scenario (Section 7.4)
Fast charge time	Decreases from 30 to 5 minutes between July 2014 and June 2025	Decreases from 30 to 5 minutes between July 2014 and June 2025
Battery price	Decreases from €500/kWh to €150/kWh between July 2014 and June 2025	Decreases from €500/kWh to €150/kWh between July 2014 and June 2025
Taxes	€0 for all electric vehicles	€0 for zero-emission vehicles

Figure 11 shows the average results over 30 runs of the *MultiPolicy-EV* and *MultiPolicy-BEV only* scenarios. Under the conditions of the *MultiPolicy-EV* scenario, there are noticeably more PHEV owners compared to the default scenario (*MultiPolicy-EV*: 14.67%, default: 10.45%) and thrice as many BEV owners (*MultiPolicy-EV*: 6.14%, default: 2.03%). This means that instead of 12.5% of the agent population owning an electric vehicle, 20.8% drives an electric car by the year 2025. Although both types of electric vehicles contribute to the absolute increase in EV sales equally, proportion-wise, these measures that benefit all electric vehicles have a larger influence on the diffusion of BEVs than that of PHEVs.

What happens when measures are specifically targeted at stimulating the diffusion of BEVs is shown in Figure 9b. BEV sales start increasing halfway 2015,

similar to the *MultiPolicy-EV* scenario. However, instead of levelling down one year later, the adoption of BEVs keeps growing and overtakes the diffusion of PHEVs halfway 2017. PHEV sales consequently lag behind and do not reach the same numbers as in the default scenario. At the end of the scenario, there are 39% less PHEV owners (6.44%) compared to the default scenario, but 667% additional BEV adopters (15.53%).

The outcome indicates that with the right combination of measures, for instance those that stimulate the adoption of zero-emission vehicles only, it is possible for BEVs to become more attractive and better sold than PHEVs within a relatively short period of time. As the single-policy scenarios showed, it is unlikely that a single measure or policy can realize this change.

It is important to note that further inspection of the behavior of the STECCAR model under both *MultiPolicy* scenarios shows that these scenarios push the technical limits of what can be simulated with the current version of the model. For most agents that adopt an EV, satisfaction levels increase to such an extent that they lose the motivation to purchase new vehicles. The agent's satisfaction is solely based on the performance of the car, given a particular propulsion system; a motivation to purchase a new car because of 'newness' or 'coolness' is excluded. As an aside, Kangur (2014) shows that adding additional needs that make agents desire newer or 'cooler' vehicles will stimulate a more speedy replacement of cars, and hence this adaptation of the STECCAR model could enhance the model's viability during long-term scenarios.

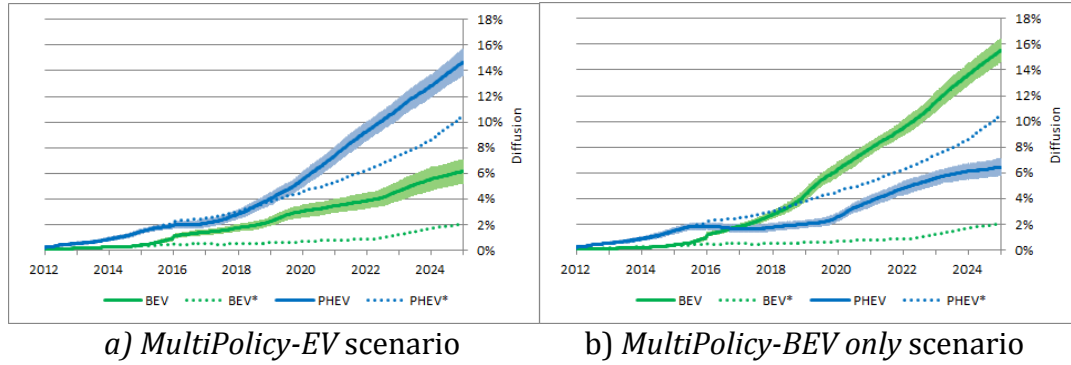


Figure 11: Diffusion of PHEVs and BEVs in the MultiPolicy -EV and MultiPolicy-BEV only scenarios in which multiple policies are combined to stimulate the diffusion of all low carbon emission vehicles or only zero-carbon emission vehicles, respectively. The solid line represents the average diffusion over thirty runs, the lighter area represents the standard deviation at each moment. The average diffusion process during the default scenario is added for reference (dotted line).

10: Discussion

In this paper, we have presented an agent-based social simulation model built to explore the diffusion process of electric vehicles in a Dutch market. Available cross-section survey data was used to calibrate the model with success, and the results obtained shed light on a number of possible diffusion patterns depending

on the policy regimes. Special attention has been paid to the differences in policy stringency: ‘loose’ policy targeting various types of low-emission EV’s versus ‘stringent’ policy targeting exclusively zero-emission vehicles, full battery electric vehicles. The model has been validated relative to the current situation of EV diffusion in the Netherlands; however, the validation of model outcomes concerning the entire diffusion process needs to be done on the basis of factual diffusion data, which has been lacking so far. Hence the validation of social simulation models using statistical data remains a complicated matter, since replicating historical data on diffusion processes does not imply that the underlying processes are correctly modelled (for an extensive discussion on validation of social simulation models see e.g. Moss, 2008). Notwithstanding those fundamental limitations, our observation that our model fits the data quite well is an indicator of the model’s performance.

This social simulation model demonstrates how a theory-based agent architecture contributes to using cross-sectional survey data in a numerical experiment that explores scenarios corresponding to a longer time period, namely more than ten years. In contrast to policy models that are based on a uniform economically optimizing actor, the Consumat approach used in this paper models agents with different needs that engage in a variety of types of decision making. It appears that a more behaviorally valid simulation approach contributes to a better understanding of the behavioral dynamics in the domain in question. Alternatively, whereas many psychological studies focus on the effects of a selected number of antecedents, such as the effects of informational strategies on attitudes and behavior in a confined setting, the Consumat approach allows for an integration of more complex behavioral rules in a multidisciplinary modeling context. Here, technology development, economic policy and behavioral effects are all studied together. Hence, where psychological models can accurately pinpoint bottlenecks in the current uptake of EVs by the average consumer, an agent-based model can intuitively help discover in which combinations and in which temporal order these constraints should be dealt with.

We have found that single measure scenarios provided hypotheses for several policy implications. First of all, they suggest that low company car tax for lessees is more important for the stimulation of BEV adoption than for PHEV adoption. Reinstating zero company car tax for all EVs has no strong effect on the long-term adoption rates of either fuel technology in the simulation. However, reinstating zero company car tax for BEVs only strongly increases the proportion of BEV owners while the total number of EV owners does not change. This indicates that - considering the significant fuel consumption of PHEVs - a larger carbon emission reduction could be obtained by applying favourable company car tax policies solely to BEVs. Second, the simulation suggests that a rise in fuel costs or decrease in fast charge electricity costs does not have a noticeable effect on the diffusion of either type of EVs by themselves. Subsequent numerical experiments showed that these policies could become more effective when combined with other measures, such as increasing the density of fast charge stations. A third result is that purchase subsidies increase the total number of EV owners in the simulation. By targeting all EVs, a higher total adoption will be reached, but this increase is almost entirely due to higher

PHEV sales. If only BEVs are targeted with purchase subsidies, BEV sales increase far more, while PHEV sales are unaffected. This suggests that financial policies aimed at all EVs would mostly benefit PHEV adoption, while financial policies targeting BEVs alone benefit the adoption of BEVs, but do not hurt PHEVs. In addition, the simulation showed that a prompt introduction of a fast charge network (within 2 years, rather than 11 years) positively influences the adoption of BEVs without noticeably altering the diffusion of PHEVs.

Whereas only a limited number of numerical experiments have been presented in this paper, the social simulation model allows for conducting a virtually unlimited number of experiments, using varying combinations of different technological, financial and informational strategies in different sequential orders. As such, social simulations open the possibility of conducting policy games with the model, where different policy scenarios can be implemented, and the simulation outcomes can be used to select and improve particular policy scenarios (see, for example, Jager & Van der Vegt, 2015).

A first conclusion that we derive from this study is that effective policy requires a combination of different policy measures (see Section 9), both monetary and structural ones. Using the STECCAR model, we have identified policy mixtures that provide a larger effect than the sum of the effects of single policies. In particular, the combination of excise duties on gasoline, subsidies for electric charging and a national fast charging network leads to a higher BEV market share than the sum of those individual measures.

Second, the results based on the STECCAR model suggest the importance of the temporal order of policies. The purchase subsidies scenario showed that by advancing the introduction of lower prices for BEVs, a comparable impact is not immediately reached. Instead, it seems crucial that other measures precede this introduction, such as putting in place an effective charging infrastructure. Because the investment in infrastructure provides a clear signal (e.g., Nyborg et al, 2016) and makes the BEV a more feasible alternative for fuel cars, it can be expected that starting with an infrastructural investment followed by financial incentives will have stronger effects than implementing them in reverse order. Additional experiments could focus in more detail on such temporal effects, exploring optimal temporal sequences of implementation.

Related to that, our third conclusion is that numerical experiments with the social simulation model show that effective policy requires a long-term vision. Both the combinations of several measures and the temporal order of measures have a long-term effect, and therefore policymakers are required to look decades ahead and plan accordingly right from the start. Rather than changing the financial regimes for fuel cars, BEVs and PHEVs and adapting the financial regime on the basis of yearly sales, it proves to be much more effective to set a goal concerning the market share of electric vehicles and to explore how the car market and infrastructure can be managed early on to reach this target.

Fourth, our results show the importance of chosen targets for policy interventions. Stimulating the sales of new PHEVs may not be effective if in practice they mainly run on fuel, and essentially crowd-out BEVs on the primary market and on the used car market. Whereas the sales of PHEVs may be considered to be a success, from the perspective of reducing emissions it is expected to be more effective to stimulate only BEVs, as is the case in Norway, in

order to achieve higher reductions in tailpipe greenhouse gases (such as carbon dioxide and nitrogen oxides) and particulate matter emissions. Our results show that specific policy measures may substantially shift the preferences of EV owners from PHEVs to BEVs. Overall, comparison of various scenarios has proven that certain measures were more effective in stimulating the extent of EV adoption to the market (for example, purchase subsidies and extended charging infrastructure), while other measures mainly regulated the ratio between the adopted PHEVs and BEVs (for example, the company car tax applied to lease vehicle use).

Some important reservations need to be highlighted as well. Obviously, models such as STECCAR are based on a lot of – sometimes crude – assumptions. Moreover, many uncertainties exist concerning future developments in the transportation sector in response to the energy-transition, technology development and acceptance, and the development of public, private and sharing transportation modalities. One should therefore not consider STECCAR as a predictive tool. Factual diffusion patterns may differ from predicted ones due to a number of reasons, such as structural changes, changes in preferences and variables or processes that are important for diffusion but not included in the model. We are dealing with a complex system, in which non-linear developments may happen due to unexpected developments.

An additional limitation is that only a selection of numerical experiments has been presented in this paper, with a specific focus on the effect of policies on the overall diffusion process. Therefore, we refer the reader to Kangur (2014) for an investigation of more specific effects of single policy measures on CO₂ emissions, which has not been presented here. Also, results of some policy analyses have been performed but (purposefully) omitted in this article, as mentioned in section 9. These included the exploration of charge time reduction and battery price reduction. Other applications have not yet been performed. Perhaps most relevant of those lie in the domains of behavioral drivers of adoption, exploration of motives behind adoption, as well as exploration of the addition by the automotive market of other technologies and vehicle types. STECCAR allows for revealing the behavioral dynamics that may emerge from policies, and therefore is more suitable to study how (combinations of) policies work, rather than predicting their precise effects. We therefore foresee that a social simulation model such as STECCAR carries a high potential to shed light on a multitude of aspects.

One of the relevant topics for further investigation is the characteristics of potential EV adopters. Such an investigation may help identify important behavioral drivers, allowing to identify who the early and late adopters are, and which policies are most effective in targeting them. This opens up the possibility to explore policy scenarios in which a sequencing of policy measures is tested. In particular, this allows for testing which policies are effective to address first adopters, and how consecutive policies can address later adopters, addressing both the first-order effects of the policy as well as the second-order effects originating from the adoption by the innovators. This may contribute to the identification of so-called “tipping points” in social systems that offer promising possibilities for policy (see e.g. Nyborg et al, 2017). STECCAR thus allows for

including second-order effects such as setting behavioral examples, sharing experiences and setting norms by the innovators in testing how policies aimed at later adopters may perform in a changing social setting. By further inspecting the simulation's output, the model may also help identify how early adopters in turn affect later adopters, and which additional policies are suitable to target these later groups.

Another promising topic of future research is to explore the motives of EV consumers. Our first simulations (see Kangur 2014) already showed unexpected results for example regarding "consumerism" that appears to stimulate the transition towards a low-emission car fleet. Consumerism is described as placing a high value on material possessions, where people tend to consume more products or replace products more often than they need (e.g. in terms of functional performance). If consumers in our simulation were equipped with a desire to acquire new car models (irrespective of their functional superiority over an existing vehicle), the model shows that transition to electric vehicles would go much faster due to higher vehicle replacement rate. Although emission-wise, this electrified fleet leads to an environmental advantage, on the whole this finding is in contrast with the "green consumerism" perspective, where a prolonged use and repair of products is advocated to reduce the environmental impact of production and waste (e.g., Cohen, 2005).

One more interesting future research prospect is the exploration of new kinds of vehicles that already appear on the market and may potentially reshape the entire personal transportation paradigm. One such possibility is related to the development of autonomous vehicles that may further reduce the perceived symbolic meaning of cars, thus possibly reducing the material demands for transportation. Such shifts in perceived symbolic meaning of owning a car may contribute to a growth in car-sharing systems, thus reducing consumerism. Social simulation methods, such as agent-based models as presented in this paper may be used to explore such possible futures and define optimal conditions for implementing a system of shared autonomous vehicles.

Summing up, STECCAR is designed to model a specific complex system and to visualize the effects of social interactions both on the cross-sectional and temporal dimensions. Such a modeling tool can be seen as an accessible policy planning and hypothesis construction tool, which allows to explore diffusion dynamics with relatively low effort, as is demonstrated for the diffusion of environmentally friendly vehicles in this paper. Realizing that in a complex world many unforeseen developments may take place, the validity of the simulation model obviously cannot be guaranteed. However, as said by George Box (Box & Draper, 1987, p. 424), "All models are wrong, but some are useful". Hence we suggest that the agent-based approach to modeling behavior contributes in an integrative manner to a better understanding of diffusion processes of environmentally-friendly durable goods such as EVs and ways to achieve a higher adoption of these goods to the market, which in turn should contribute to more effective management of environmental issues locally, nationally and worldwide.

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